The Role of Human Development on Deforestation in Africa: A Modelling-Based Approach

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ABSTRACT

The rate of deforestation in Africa is of paramount concern not only to the future of Africa, but also to the world. This study uses country-level data to model changes in forest area over an 18 year period (1990-2007) in 35 African countries and investigates the role played by important development indicators of human development. The results reveal that the net loss of forests was 0.19% every year between 1990 and 2007. This implies a total of 3.42% of forest was lost in the 18 year period. This is more in line with estimates obtained by the Food and Agricultural Organization (0.56% between1990-2000 and 0.49% between 2000-2010). Human development which involves life expectancy, education and income is found to have a positive effect on forest growth and conservation, while cutting down trees for wood fuel is a significant cause of deforestation. Using generalized linear mixed models and generalised estimating equations, we were able to calculate expected estimates of forest area for 2010, 2020 and 2030 under the assumption that nothing is done to change observed trends. In many countries, progress has been made in reforestation, forest protection and conservation. However, if indiscriminate cutting down of trees is not checked, many countries will lose most or all of their forests by 2030.

JEL Classification: C33; C36; C50; O13; Q23; I10

Keywords: Deforestation; Environment; Human development index; Agriculture; Data modelling; Africa

1. INTRODUCTION

Human development has long been thought to have an influence on rainforest degradation. The effect of many micro and macro-economic factors on forest degradation has been the subject of intense academic debates recently. In a review of 140 economic models on the causes of tropical deforestation, Angelson and Kaimowitz (1999) raises concern that some current economic policies may be putting pressure on tropical forests.

The State of the World's Forest Report of the Food and Agricultural Organisation (FAO) in 2010 as well as 2011 indicate a reduction in the overall trend of net forest loss in Africa between 1990 and 2010. This reduction can be credited to tree-planting and reforestation programs introduced to combat desertification, educational programs that increase awareness on protection of biodiversity and ecosystems.

Due to the high occurrence of forest fires and the rapid conversion of forest lands into agricultural lands, Africa has the second highest deforestation rate in the world during the period from 1990 to 2005 (FAO, 2005).

Changes in forest area of African countries have long been elaborated in literature. Achard et al (2002) determined forest changes between 1990 and 1997 by analysing satellite imaging data. The disturbing deforestation trends reported also confirms observations made by the FAO 1980 inventory as well as the global forest assessment of the FAO in 1980, 1990 and 2000. In a recent study, Kelatwang and Garzuglia (2006) estimated the net loss of forests at 4% per year between 1990 and 2005.

Lanly (2003) suggests that the main determinants of deforestation in tropical and subtropical countries include the subsistence and plantation agriculture, cattle ranching, firewood use, timber exploitation as well as mining and road projects. Since the economies of these countries are based to a large extend on these activities, their Human Development Index (HDI) indices can uniquely capture the human activities that directly or indirectly affect the forest area. A recent study of the effect of human development on deforestation in biodiversity hotspots by Jha and Bawa (2005) uses correlation analysis to show that the pressure on the forests could be increased in countries with low development.

In this paper, we begin by shedding light on the design features, data and the characteristics of the variables involved (Section 2). We then examine the distribution of forests in Africa and underscore its size in the Congo basin. In the methodology (Section 3), we describe the models used in the analyses and present the results in Section 4. The interpretation of these results has been detailed in discussion (Section 5) followed by conclusion in Section 6.

2. STUDY DESIGN, DATA AND VARIABLE CHARACTERISTICS

In order to understand current trends of deforestation in Africa, data was collected for 35 African countries during the period 1990 – 2007. The motivation for selecting many countries is to draw attention to country-level changes in the proportion of forest land and enable an assessment on the effects of forest conservation and reforestation policies. The period was chosen solely because of data availability of the indicators of interest. Since individual countries designate their own areas of forest conservation, reforestation and lumbering (in the case of legal economic activities), it is of interest to grasp the dynamics of changing forest sizes especially during a period when many African countries enacted new forest conservation laws.

The study design is longitudinal and hierarchical as the same indicators which are measured several times (1990-2007) are nested within the countries.

The variables and their characteristics are described in Table 1

Table 1: Description of indicator variables

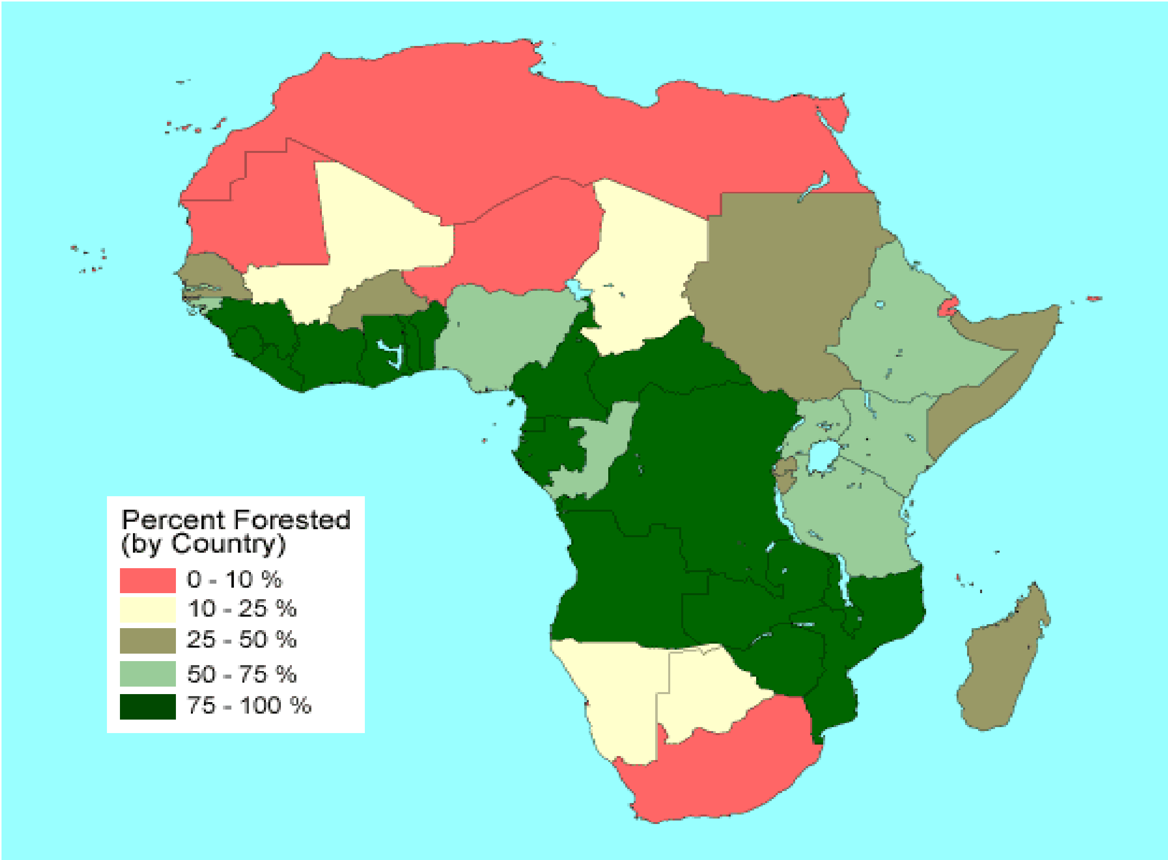
Indicator name	Source
Forest Area	Food and Agriculture Organization/World Bank
Inequality adjusted Human Development Index	United Nations Development Program
Agricultural Land	Food and Agriculture Organization/World Bank
Forest Products Exports	Food and Agriculture Organization/World Bank
Ores and Metals Exports	United Nations Statistics Division/World Bank
Wood Fuel Production	Food and Agriculture Organization/World Bank

Forest Area is the percentage of land area occupied by forests (World Bank, 2011). The Inequality-adjusted HDI is the human development index adjusted for inequalities (see Fosta et al, 2003 and UNDP, 2010). Agricultural land is the proportion of land used for subsistence and commercial agriculture as well as pasture (World Bank, 2011). Forest products exports include medicinal and food plants, fruits, oils, honey among others (see Anderson et al, 1999) in US$. Ores and metals exports include commodities in Standard International Trade Classification sections 27 (crude fertilizer, minerals); 28 (metalliferous ores, scrap); and 68 (non-ferrous metals) as a percentage of merchandize exports (see World Bank, 2011). Wood fuel production involves amount of wood carbonized by partial combustion or application of heat from an external source. It is used as a fuel or for other uses. Figures are given in weights of metric tons (see World Bank, 2011).

DISTRIBUTION OF AFRICAN FORESTS

Most of the forests in Africa are located within the tropical region. We observe in Figure 1 that the Congo basin represents the vast proportion of forest area with its countries (Cameroon, Equatorial Guinea, Gabon, Congo Republic, Central African Republic and the Democratic Republic of Congo) having about 75% or more of the land area covered by forests. North African countries and South Africa have less than 10% of their land areas covered by forests. In east Africa, the land areas are only moderately occupied by forests. This distribution has seen considerable changes in recent times, most of which has resulted in vast net losses of forest area (see Figure 2)

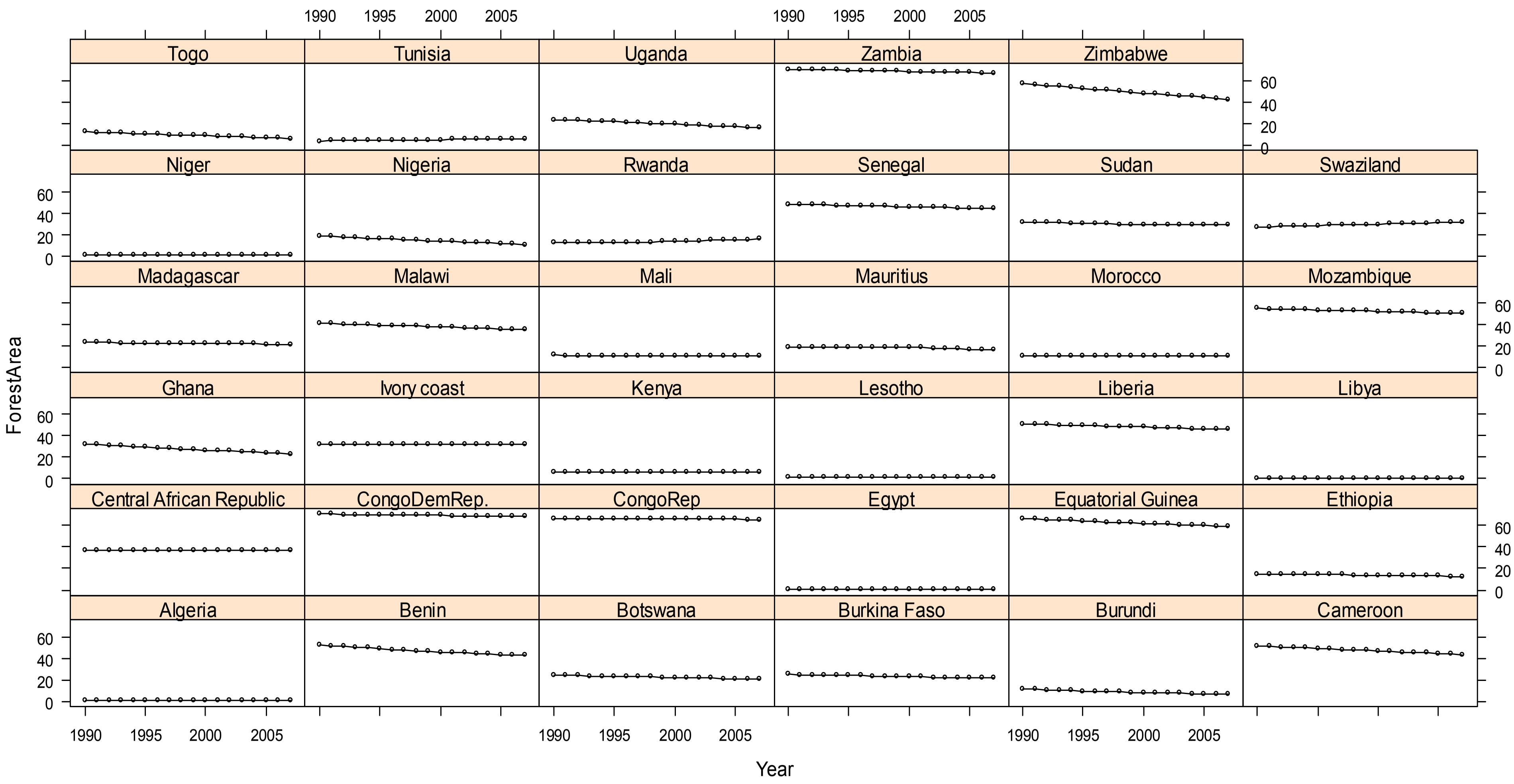
Figure 1: Distribution of forests as percentage of forested land by country



Courtesy of Brown and Gaston (1996) Carbon Dioxide Information Analysis Center, U.S. Department of Energy, Oak Ridge National Laboratory, Oak Ridge, Tennessee, U.S.A.

The plots in Figure 2 show that countries of the Congo basin have the largest forest areas while North African countries have the smallest forest areas. Although the forest areas of a few countries remain relatively the same over the time period, those of most countries show drastic reductions over the time period. There is already serious concern in countries like Togo, Uganda, Zimbabwe, Nigeria, Malawi, Mozambique, Ghana, Liberia, Equatorial Guinea, Benin and Cameroon about the rate of forest loss. In other countries, like Tunisia, Niger, Mali, Morocco, Mauritius, Lesotho, Kenya, Egypt, Ethiopia, Algeria and Burundi, the situation is already critical.

Figure 2: Evolution of forest area in 35 African countries between 1990 and 2007



3. METHODOLOGY

Modelling the mean response as a function of the covariates could be a challenging task because, unlike in the classical situation where data are assumed to be independent, we wish to capture and characterize the time trend of forest size within and between countries as well as the average trend of all the 35 countries.

The data for the Forest Products Exports and Wood Fuel Production were transformed on a logarithmic scale.

MODELLING COUNTRY-SPECIFIC FOREST AREA PROFILES

Due to the longitudinal nature of the data, conventional multivariate methods cannot be used for analysis. Classical analysis of variance models (ANOVA) and multivariate analysis of variance (MANOVA) are not parsimonious since they do not capture individual random effects and therefore are restrictive. Verbeke and Molenberghs (2009) suggests the use of linear regression functions to approximate individual longitudinal profiles. In order to do this, a two-stage analysis has been introduced by many statisticians. Kackar R. and Harville D. (1981), Burns and Giesbrecht (1985), Laird and Ware (1982) have all shown that the two-stage estimation and prediction methods for mixed models is unbiased. In this model, subject-specific regression coefficients are obtained in the first level and in the second level, they are related to the covariates using multivariate regression methods.

MODEL SPECIFICATION

The model known as the general linear mixed model is obtained by combining the two stages.

The stage 1 model can be written as follows:

$$Y_{ij} = \beta_{1i} + \beta_{2i} t_{ij} + \varepsilon_{ij} \dots\dots\dots\dots\dots\dots\dots\dots\dots. \quad (1)$$

Where Y_{ij} is the forest area of the ith country at the jth time point, β_{1i} and β_{2i} are the intercept and slope respectively of each country. These are also the fixed effects parameters. t_{ij} is the time effect and ε_{ij} are random error terms.

The stage 2 models are derived from stage 1 fixed effects in Eqn (1) to accommodate country specific intercept and slope.

$$\begin{cases} \beta_{1i} = \beta_0 + b_{1i} \\ \beta_{2i} = \beta_1 X_i + b_{2i} \end{cases} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(2)$$

The combined model described in Verbeke and Molenberghs (2009) is given as follows:

$$Y_{ij} = (\beta_0 + b_{1i}) + (\beta_1 X_i + b_{2i}) t_{ij} + \varepsilon_{ij} \dots\dots\dots\dots\dots.\dots.(3)$$

With the inclusion of the random effects of the intercept and slope, Hedeker (2004) shows that the population distribution of the intercept and slope can be assumed to be bivariate normal with mean and variance-covariance matrix of the random components given as:

$$\Sigma_b = \begin{bmatrix} \sigma_{b_1}^2 & \sigma_{b_1 b_2} \\ \sigma_{b_1 b_2} & \sigma_{b_2}^2 \end{bmatrix} \dots\dots\dots\dots\dots\dots\dots\dots.(4)$$

This model is very conducive because it allows for situations in which forest size remains constant over time as well as changes in forest size over time.

Selection of the best fitting model was done on the basis of the Akaike Information Criterion (AIC). The AIC (Akaike, 1974) is given as follows.

$$AIC = -2 Log\ Likelihood + 2K$$

Where $-2Log\ Likelihood$ is twice the difference in the log likelihood of the null model and the alternative model (Neyman and Pearson, 1928) and K is the number of parameters. The AIC uses deviance to measure model fit by penalizing for complexity. Since the sample size is small ($\frac{n}{k} \geq 40$), it is necessary to avoid bias by correcting for sample size. The corrected AIC is given as

$$AIC_c = -2Log\ Likelihood + 2K + \frac{2K(K+1)}{(n-K-1)}$$

Where n is the sample size.

One important variant of the AIC is the QIC (Quasi likelihood Information Criterion). The QIC allows the use of different working correlations to estimate GEE parameters (Pan, 2001)

MODELLING THE AVERAGE FOREST AREA PROFILE

Another way of evaluating the trend in forest area in Africa is by fitting a model to the data that captures the average trend of all countries. Liang and Zeger (1986) proposed an extension of generalized estimating equations (GEEs) to model longitudinal data. This method involves the consistent estimation of regression parameters by quasi likelihood without specification of joint distribution of the outcomes. Instead of maximizing the likelihood as in the case of general linear mixed models, GEEs use the mean and variance (first and second moments) as estimating equations which are independent when within-country observations are independent, or could assume any correlation structure. Application of GEEs to longitudinal data was elaborated by Dunlop (1994) in which estimating equations for the mean were shown to be identical to the generalized least squares. The GEE approach by Liang and Zeger (1986) uses estimating equations under weak assumptions about the joint distribution to obtain consistent estimates of the regression parameters.

For the forest area data, we fitted a GEE model with exchangeable working correlation matrix (assumes the same correlation for all observations within each country). Even though there are concerns of efficiency when the correlation structure is not correctly specified, Molenberghs and Verbeke (2005) highlight the fact that parameter estimates are consistent. Since the mean and covariance do not necessarily have to be correctly specified, the empirical (robust) variance estimator was used to estimate the parameters.

4. RESULTS

Models with Linear effect of time was fitted and compared to models with quadratic and cubic effects of time. Table 2 shows that not only is the deviance smallest (LRT chi-square) in the model with the linear time effect, but also it's not necessary to include a quadratic and cubic effect (AIC is 135.4 for quadratic effect and 138.6 for cubic effect).

Table 2: Fit statisctics for model time effects.

	Time Effects		
	Linear (Year)	Quadratic (Year^2)	Cubic (Year^3)
-2 Log Likelihood	137.2	147.4	150.6
AIC_c	125.2	135.4	138.6
LRT Chi-square	5773.68	5784.03	5787.35
LRT df	3	3	3
LRT P-value	< 0.0001	< 0.0001	< 0.0001

$-2Log\ Likelihood$ is twice the difference in the log likelihood of the null model and the alternative model LRT is the Likelihood ratio test. The alternative model is the model with the effect (Neyman and Pearson, 1928). The AIC_c is the Akaike Information Criterion (Akaike, 1974) with sample size correction. In LRT df represents the degree of freedom of Null model likelihood ratio test and the p-values are their extreme probabilities. All three time effects have significant $\chi 2$/df (p-value <0.005).

The total number of countries selected for this study was 35. Selection was based on availability of data for the indicators of human development. Of this number,

The fit statistics of the random intercepts model (AIC_c=2367.3), random slopes model (AIC_c = 5038.4) and Random slopes has a poorer fit relative to the random intercepts. When both the random intercepts and random slopes were included in the same model, the fit was much better (*AIC_c= 125.0*) and. Based on these statistics, the best fitting country-specific model is the random intercepts and slopes model. Inclusion of covariates greatly reduced the variability and improved the fit of the model (*AIC_c= 37.4*)

The variance estimate of the random intercepts, $\sigma_{b_1}^2$, is 491.13 (SE 117.44) while that of the random slopes, $\sigma_{b_2}^2$ is 0.062 (SE 0.02) These correspond to the variance of the intercepts and slopes respectively of all 35 countries. The covariance of the random intercepts and slopes, $\sigma_{b_1 b_2}$, is -2.91 (S.E. 1.16). The negative estimate indicates that the relationship is negative with higher intercepts leading to lower slopes. This explains the reducing trend of forest areas over the years. The estimates of these random effects are shown in the appendix (Table 7). 18 out of the 35 countries show a net gain or an approximate no net change in forest area over the time period. In 17 countries, there was a net loss of forest area over the time period.

The correlations of fixed effects are shown in the appendix (Table 6). Since the correlations are very low, it can be assumed that no effect in the model can be sufficiently accounted for by another. Multicollinearity is therefore not a problem.

5. DISCUSSION

In the country-specific model with random intercepts and slopes, the effect of time is negative implying a decreasing trend of forest area over the years. This negative relationship is also captured by the GEE, although in this case, is not significant. In the GLMM, the average rate of deforestation, if we control for other endogenous factors was 0.19% every year from 1990 to 2007. Based on the GEE, 0.24% of forest area was lost every year during the period of the study. Both models give approximately the same estimates.

Table 3: Fitted models and parameter estimates

Parameter	Random Intercept	Random Slope	Random Intercept and slope	Random intercept and slope with covariates	GEE with Exchangeable working correlation
Intercept	29.04(3.58)*	29.04(0.90)*	29.04(3.73)*	26.91(3.78)*	28.10 (7.42)*
Year	-0.18(0.009)*	-0.18(0.31)	-0.18(0.04)*	-0.19(0.04)*	-0.24 (0.06)*
IneqadjHDI				1.47(0.76)*	28.18 (10.30)*
AgricLand				0.004(0.007)	-0.23 (0.09)
LogForestPrEx				0.006(0.005)	-0.04 (0.04)
OresMetalsEx				0.00004(0.001)	-0.02 (0.01)
LogWoodFuelPr				0.08(0.02)*	-0.01 (0.01)
-2LogLikelihood	2359.2	5030.3	137.2	14.7	
AIC_c	2367.3	5038.4	125.0	37.4	395.88[#]
Null LRT Chi-square	3277.26	606.21	5773.68	3129.15	
Null LRT DF	1	1	3	3	
Null LRT P-value	<0.0001	<0.0001	<0.0001	<0.0001	

AICc is the Akaike information criterion corrected for sample size. The QIC is the quasi likelihood equivalence of the AIC

Table 4: The covariance structure of the Random intercepts and slopes model with covariates and interaction

Covariance Parameter	Subject	Estimate	Std Error	Pr>/ Z/
$\sigma_{b_1}^2$	Country	491.13	117.44	<.0001
$\sigma_{b_1 b_2}$	Country	-2.9106	1.1561	0.0118
$\sigma_{b_2}^2$	Country	0.06208	0.01626	<.0001
Residual		0.01078	0.00087	<.0001

The $\sigma_{b_1}^2$ and $\sigma_{b_2}^2$ are the variance of the random intercepts and slopes respectively. They have covariance $\sigma_{b_1 b_2}$

Table 5: Determined estimates of forest area and projected estimates under similar conditions

	Determined Estimates of Forest Area		Projected Estimates of Forest Area if endogenous variables are unchanged		
Country	1990	2000	2010	2020	2030
Algeria	0.69	0.66	0.58	0.50	0.42
Benin	52.08	45.75	38.43	31.13	23.83
Botswana	24.21	22.12	20.02	17.92	15.82
Burkina Faso	25.03	22.84	20.64	18.44	16.24
Burundi	11.25	7.71	2.75	0.00	0.00
Cameroon	51.54	46.79	42.19	37.59	32.99
Central African Rep	37.25	36.76	36.36	35.96	35.55
Congo Dem. Rep	70.74	69.36	69.36	69.36	69.36
Congo Rep	66.50	66.05	65.55	65.05	64.55
Ivory coast	32.14	32.47	35.57	28.67	41.77
Egypt	0.045	0.059	0.109	0.159	0.209
Equatorial Guinea	66.31	62.13	62.13	62.13	62.13
Ethiopia	15.20	13.71	12.31	10.91	9.51
Ghana	32.73	26.78	14.78	2.78	0.00
Kenya	6.52	6.29	5.89	5.49	5.09
Lesotho	1.32	1.38	1.39	1.40	1.41
Liberia	51.17	48.06	48.06	58.06	48.06
Libya	0.12	0.12	0.12	0.12	0.12
Madagascar	23.54	22.56	21.56	20.56	19.56
Malawi	41.41	37.91	36.31	34.71	33.11
Mali	11.53	10.88	10.23	9.58	8.93
Mauritius	19.11	19.06	14.3	9.00	3.37
Morocco	11.31	11.24	10.36	9.48	8.60
Mozambique	55.16	52.38	49.58	46.78	43.98
Niger	1.54	1.05	0.00	0.00	0.00
Nigeria	18.92	14.42	9.82	5.22	0.62
Rwanda	12.89	13.94	17.74	21.54	25.34
Senegal	48.55	46.22	46.02	45.82	45.62
Sudan	32.15	29.67	29.44	29.21	28.98
Swaziland	27.44	30.12	27.72	25.32	22.92
Togo	12.59	8.94	5.34	1.74	0.00
Tunisia	4.14	5.39	7.89	10.39	12.89
Uganda	24.10	19.63	15.03	10.43	5.83
Zambia	71.03	68.78	66.65	64.30	62.06
Zimbabwe	57.29	48.84	40.34	31.84	23.34

Estimates for 2010, 2020 and 2030 are based on the average model for each country. The assumption made is that the rate of change of forest area remains the same for each year.

Inequality adjusted HDI, the indicator for human development has a positive effects on forest area. It is statistically significant in the GEE as well as the GLMM (Pr>/t/<0.005). This relationship reflects the importance of improving on the various aspects of human development for individual countries. Improving the contributing factors of the Inequality adjusted HDI (Life expectancy, education and income) would therefore play a significant role in reducing deforestation in these countries.

Ores and metal exports as well as wood fuel production both have a negative effect on forest area even though these effects are not significant at the 5% level. The negative direction of their effects confirms the logical explanation that irresponsibly cutting down trees from the forests for firewood is damaging to the sustainability of the forests. Ores and metals are mostly mined from lands occupied by forests. This is evident in countries like Zimbabwe, Zambia and South Africa (Not included in the study) whose economies partly rely on the mining sector. The larger the size of the Agricultural land, the more prominent it is that there is a loss of forest area. Countries that have introduced or expanded agricultural lands for plantations and livestock have had to resort to deforestation.

The negative effects of Ores and mineral exports, wood fuel production and agricultural land were not captured by the generalized linear mixed model. However, the estimates are very small (≈ 0).

In Table 4, projections of forest area have been made based on the assumption the same *status quo* (covariates do not change) prevails. If serious measures are not taken to reverse the trend, countries like Burundi, Ghana, Niger, Nigeria and Togo will have little or no forests left by the year 2030. Also, despite the reforestation programs introduced to fight desertification like the Sahara Forest Project, the Keita project in Niger (Vecchia et al, 2005) and projects in other countries, very little has been achieved on the ground. The Keita project however has increased the agricultural productivity of Niger but more has to be done in the area of reforestation. Jha and Bawa (2005) identified low human development as the leading cause of high deforestation in Benin and Nigeria due to high dependence on firewood and unreliable agriculture.

Based on the projections on Table 4, the future of the African forest conservation remains grim if human development does not improve. Many programs have been initiated to reverse the trend of forest loss. FAO regional strategic framework for Africa has mobilized resources from 1996 and 2009 World Food Summit, The Millennium Declaration, Accra Agenda for Action, L'Aquila Food Security Initiative (FAO-RAF 2006). However, according to the UN world summit Declaration (2005), Africa remains the only continent which is not on track to meet any of the goals of the Millennium Declaration (Easterly, 2007). This implies that, unless drastic actions are taken, the net loss of forest area will continue into the future.

Even though the level of human development significantly determines the rate of forest loss in the countries involved in this study, we must however be cautious not to generalise the concept. Many studies including Asongu and Jingwa (2011) have also shown that rapid population growth contributes to increasing pressure on forests.

6. CONCLUSION

In this study, we proposed two approaches to model changes in forest area in 35 African countries during the period 1990-2007. Country-specific Generalised linear mixed, models which allow for individual country profiles to be taken into account. Generalised estimating equations (GEEs) were used to estimate the parameters at the population level. Both the model with country specific effects and the average model show that forest area reduces over time. The results of the analysis also show that more forest area can be conserved if the inequality adjusted Human Development Index increases. Furthermore, country-specific profiles were used to project estimates of forest areas assuming that the same conditions prevail. This can be used as a basis of evaluating the effectiveness of programs put in place to overcome deforestation. The results of this study are more in line with the estimates of forest loss realised by the FAO and differences observed are the result of a smaller sample of 35 countries.

APPENDIX

Table 6: Correlations of fixed effects.

Effect	Intercept	Year	IneqAdjHDI	AgricLand	LogForestPrEx	OresMetalsEx	LogWoodFuelPr
Intercept	1.00						
Year	-0.49	1.00					
IneqAdjHDI	-0.07	-0.06	1.00				
AgricLand	-0.09	-0.04	-0.05	1.00			
LogForestPrEx	-0.01	-0.02	0.00	0.06	1.00		
OresMetalsEx	0.01	0.00	-0.12	-0.01	0.10	1.00	
LogWoodFuelPr	-0.08	-0.01	-0.06	0.16	-0.12	-0.05	1.00

Forest Area is the percentage of land area occupied by forests (World Bank, 2011). The Inequality-adjusted HDI is the human development index adjusted for inequalities (see Fosta et al, 2003 and UNDP, 2010). Agricultural land is the proportion of land used for subsistence and commercial agriculture as well as pasture (World Bank, 2011). Forest products exports include medicinal and food plants, fruits, oils, honey among others (see Anderson et al, 1999) in US$. Ores and metals exports include commodities in Standard International Trade Classification sections 27 (crude fertilizer, minerals); 28 (metalliferous ores, scrap); and 68 (non-ferrous metals) as a percentage of merchandize exports (see World Bank, 2011). Wood fuel production involves amount of wood carbonized by partial combustion or application of heat from an external source. It is used as a fuel or for other uses. Figures are given in weight in metric tons (see World Bank, 2011).

Table 7: Random effects Estimates and standard errors by country.

Country	Intercept	Slope (Year)
Algeria	-28.46 (3.75)*	0.18 (0.04)*
Benin	22.45(3.75)*	-0.33 (0.05)*
Botswana	-4.76(3.75)	-0.03 (0.05)
Burkina Faso	-3.64 (3.75)	-0.04 (0.05)
Burundi	-18.14 (3.76)*	-0.07 (0.04)
Cameroon	22.45 (3.75)*	-0.27 (0.04)*
Central African Rep	8.66 (3.76)*	0.15 (0.04)*
Congo Dem. Rep	41.82 (3.75)*	-0.25 (0.21)
Congo Rep	37.84 (3.76)*	0.09 (0.08)
Ivory coast	3.03 (3.75)	0.23 (0.04)*
Egypt	-29.06 (3.76)*	0.18 (0.04)*
Equatorial Guinea	37.79 (3.75)*	-0.22 (0.21)
Ethiopia	-13.45 (3.80)*	0.02 (0.01)
Ghana	3.37 (3.75)	-0.37 (0.04)*
Kenya	-22.68 (3.75)*	0.17 (0.04)*
Lesotho	-27.73(3.78)*	0.20 (0.05)*
Liberia	22.55 (3.75)*	-0.13 (0.21)
Libya	-28.95 (3.87)*	0.18 (0.13)
Madagascar	-5.47 (3.75)	0.08 (0.04)
Malawi	12.53 (3.75)*	-0.16 (0.04)*
Mali	-17.05 (3.75)*	0.11 (0.05)*
Mauritius	-9.23 (3.75)*	0.06 (0.04)
Morocco	-17.87 (3.75)*	0.20 (0.04)*
Mozambique	26.34 (3.75)*	-0.10 (0.05)*
Niger	-27.13 (3.75)*	0.15 (0.04)*
Nigeria	-10.29 (3.75)	-0.27 (0.04)*
Rwanda	-18.25 (3.82)*	0.51 (0.06)*
Senegal	19.66 (3.75)*	-0.05 (0.04)
Sudan	0.94 (3.75)	0.15 (0.05)*
Swaziland	-1.53 (3.76)	0.45 (0.05)*
Togo	-16.37 (3.75)*	-0.18 (0.04)*
Tunisia	-25.05 (3.75)*	0.30 (0.04)*
Uganda	-4.89 (3.75)	-0.27 (0.04)*
Zambia	42.13 (3.75)*	-0.03 (0.04)
Zimbabwe	28.43 (3.75)*	-0.64 (0.05)*

*Pr>/t/ is <0.005 and hence significant at the 5% level. Standard errors are predicted.

Countries with net loss of forest area between 1990 and 2007

Countries with net gain or no net change of forest area between

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